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Hybrid Learning Assisted Abstraction for Service Performance Assessment Over Multi-Domain Optical Networks

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Abstract: This paper demonstrates the field-trial validation for a novel machine learning-assisted lightpath abstraction strategy in multi-domain optical network scenarios. The proposed abstraction framework shows high accuracy for dynamic optical networks with 0.44 dB estimation error.

1. Introduction

Software-defined and programmable optical networking have received a wide range of attention in recent years as key technology enablers for dynamic and autonomous optical networks. However, autonomous algorithms for optical networks need complex analytical models to assess the performance of the lightpaths such as Quality of Transmission (QoT). An abstraction layer to hide these complexities for the control plane can pave the way for the implementation of *intelligent* and complex *autonomous* optical networking. Most research activities focus on hardware abstraction such as an extension to Openflow/YANG. Therefore, an abstraction layer for monitoring physical layer information and mapping the parameters to certain QoT indicators is essential to allow operators to implement complex algorithms with simple abstracted information within their domains. For services across multiple optical networks, each network can deploy such an abstraction layer and exchange abstracted information while *avoiding* sharing a detailed knowledge of their networks. Machine Learning (ML) has recently attracted a huge interest in QoT prediction for enabling an abstraction layer that captures *both* network uncertainty and dynamicity, as opposed to conventional analytical models. Authors in [1] present a self-learning network to predict lightpaths QoT, which lacks accuracy for links with limited training data. Using ANNs, the works of [2-4] consider only either the number of channels or the one hot encoding of wavelength. These works *cannot* provide accurate results when addressing non-previously established wavelengths. Our work proposes a simple SNR degradation model that allows network operators to share an abstracted view of their network *without* exposing their internal organisation. In further, we propose a *hybrid* learning framework that combines deep learning (DL) and Gaussian Process Regression (GPR) to overcome the accuracy issues raised in [1-4]. Specifically, our framework learns intra-domain services using DL by leveraging its high prediction accuracy, whereas in case of absence of training data or when there are services across multiple domains, it uses GPR to avoid vast required features. We demonstrate the hybrid learning strategy through a field-trial testbed of 3 optical networks. The experimental results denote a *high SNR prediction accuracy* with an average of 0.44 dB estimation error.

2. Hybrid Learning Assisted Abstraction Model and Field-Trial Testbed Setup.

To hide the network-specific knowledge while also allowing information exchanged between different optical network domains, the SNR degradation factor $SNR_{n,l}$ (dB) is introduced as the abstracted value to be shared between multiple networks. $SNR_{n,l}$ gives the information on how the quality of the signal degrades in link *l* of network *n* in the presence of various impairments. However, it hides the details of the network such as ROADM information, fibre length, number of EDFAs, EDFA power, etc. In this case, the end-to-end performance of a lightpath is formulated as:

$$SNR_{end-end} = 10 \cdot log_{10}(\textstyle\sum_n \sum_l 1/10^{SNR_{n,l}/10} + 1/10^{SNR_{TRx}/10})^{-1} \quad (1)$$

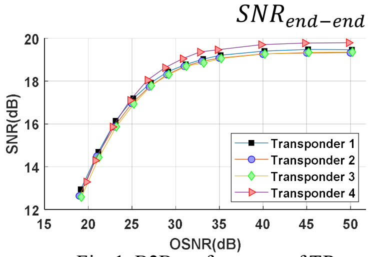

Fig. 1: B2B performance of TRx

where the SNR_{TRx} represents the performance of the transponders (TRx), usually quantified through back-to-back (B2B) measurement. In this paper, we measured the B2B performance of TRx by coupling the signal with different levels of ASE noise, leading to the different level of OSNR, as depicted in Fig. 1. The latter shows the B2B performance of partial TRx used in this experiment, indicating that all the TRx have a similar performance with an average SNR_{TRx} of 19.4 dB without ASE noise. Additionally to TRx measurements, we apply ML techniques to learn the SNR degradation factors for both intra and inter-domain services. Fig. 2 depicts the field-trial experimental testbed including 3 network domains shown as: Network 1, National Dark Fibre Facility (NDFF) and Network 3. We deploy in total 24 TRx to serve both the intra and inter-domain network services, where the lightpaths can be added and dropped via arbitrarily WSS. All the 24 TRx are able to provide dual-polarisation QPSK signal while the Voyager TRx are capable of tuning modulation format to 16QAM.

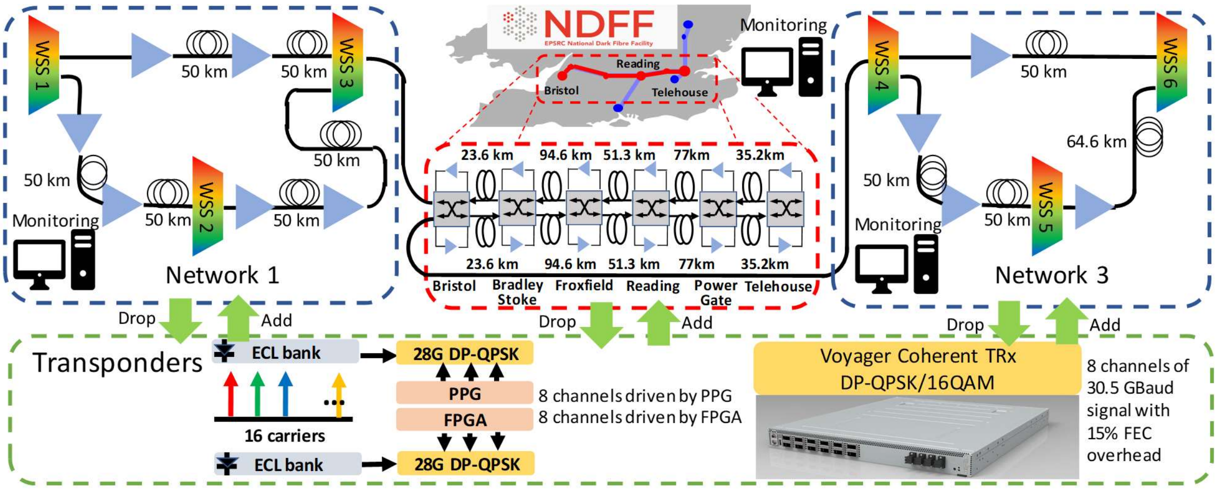

Fig. 2. Field-trial experimental testbed including 3 optical network domains with network monitoring.

The ML assisted abstraction process includes the services learning phase and the provisioning phase. In the learning phase, the DL is chosen as the tool only to learn the intra-domain services as applying DL for inter-domain services learning requires detailed knowledge to be shared among multiple parties. Features collected through monitoring vary for different networks. In NDFF, the monitoring data/features for DL contains signal launch/received power, EDFA input/output power, EDFA laser bias and one hot encoding of the wavelengths. In Network 1 and 3, different stages of the laser drive current/power in EDFA and their temperatures are included besides the above features. The DL neural networks consist of 5 hidden layers with 124 neurons in each layer and *'relu'* as the activation function. As we also normalize the output layer, *'sigmoid'* is chosen as the activation function at the output layer. For the inter-domain services, GPR is applied as it only requires the SNR performance of the service lightpaths as the training data. Therefore, it can be shared between different networks in the form of abstracted information. In the provisioning phase, network providers utilize the shared abstracted knowledge from intra and/or inter-domain services learning to assess the performance of new services using Eq. (1). For example, for a new service from network 1 to network 3 via NDFF, it can utilize the abstracted results from DL of intra-domain services of network 1, NDFF and network 3 respectively, as depicted in Fig. 6 (a). In case of absence of DL knowledge of particular wavelength/path in network 1, the new service can still utilize the abstracted information from GPR of inter-domain services between network 1 and NDFF, and the knowledge from DL of intra-domain services of network 3, as depicted in Fig. 6 (b).

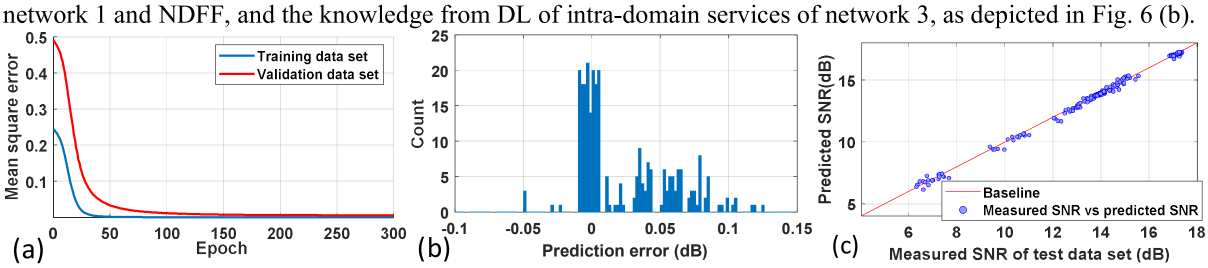

Fig. 3: Deep learning results. (a) normalised prediction mean square error against the number of training epochs; (b) distribution of prediction errors after training; (c) predicted SNR vs the measured SNR.

3. Results and Discussion

In Fig. 3, we show the overall performance of applying DL for intra-domain services learning. Fig. 3 (a) shows the mean square error of normalized prediction result reduces against the increasing number of training epoch. Fig. 3 (b) and Fig. 3 (c) depict the prediction accuracy compared to the measured value for various test scenarios which indicates most of the errors are within 0.1 dB. Fig. 4 (b) – (d) demonstrates one test scenario of using DL for intra-domain services abstraction of network 1, NDFF and network 3 respectively while their launching signal spectrum of the test scenario are shown in Fig. 4 (a). Again, DL shows high accuracy for intra-domain service learning for all 3 networks. We also apply GPR to learn the performance of inter-domain services, as shown in Fig. 5 (a) – (c), with 15, 10 and 7 training samples for inter-domain services between NDFF and network 3. From the figures, GPR can achieve prediction with average 0.6 dB error. However, accuracy improves with the increasing number of training samples. Although GPR performs slightly worse compared to DL for the abstraction, it proves to be a useful learning tool for inter-domain services training with sufficient training data.

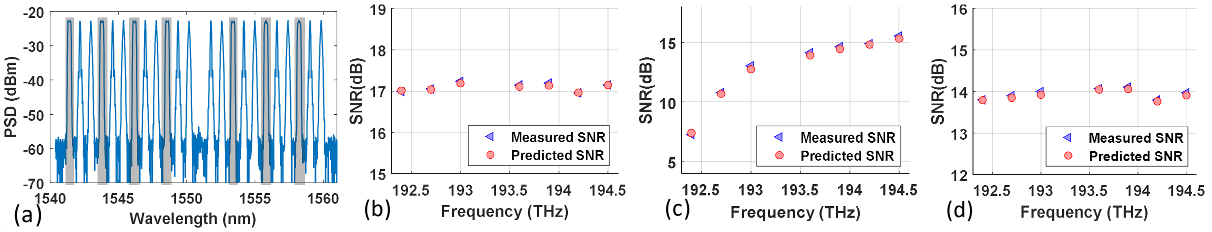

Fig. 4. SNR prediction using DL for one test scenario for intra-domain services. (a) spectrum of the test scenario. (b) predicted SNR vs measured SNR for services in network 1. (c) predicted SNR vs measured SNR for services in NDFF. (d) predicted SNR vs measured SNR for services in network 3.

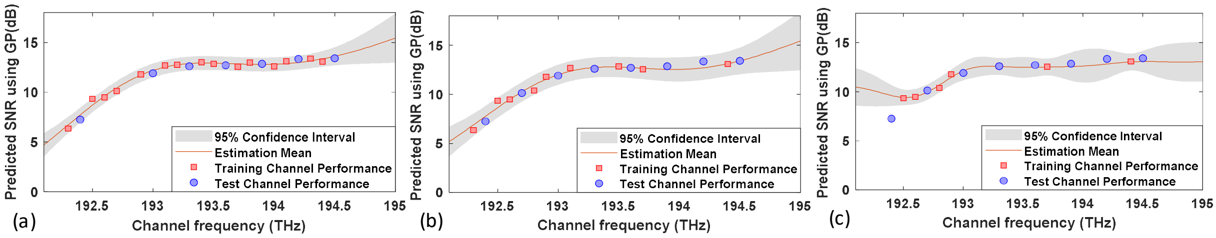

Fig. 5. GPR prediction results for network services across NDFF and network 3: (a) 15 training samples; (b) 10 training samples and (c) 7 training samples.

In the field-trial testbed, we aim to establish services between network 1 and 3 through NDFF. To predict their performance, we utilize the learning results from previously established services, both from DL of intra-domain services and GPR of inter-domain services to form the hybrid learning strategy. When all the domain level abstracted information from DL is available, they can be combined to give the estimation of end-to-end performance using Eq. (1), as shown in Fig. 6 (a). However, the domain level abstracted value of DL may not be applicable in any circumstances. In case of lacking enough training data of services of DL in network 1, we can combine the learning results from GP between network 1 and NDFF, and DL based learning results of network 3. The accuracy of the hybrid learning of using DL and GP is shown in Fig. 6 (b). A similar concept applies when NDFF or network 3 does not have DL results for the new services, the prediction is calculated based on aggregating the learning results from network 1 using DL and from NDFF-network 3 using GPR, as depicted in Fig. 6 (c). Fig. 6 (d) demonstrates the direct GPR learning of services across 3 network domains. It again shows the GRP over 3 network domains achieves slightly less accuracy than the other hybrid learning methods. The results in Fig. 6 indicate that hybrid learning assisted abstraction can serve as an accurate tool to predict the performance of new services, with the average estimation error of 0.44 dB.

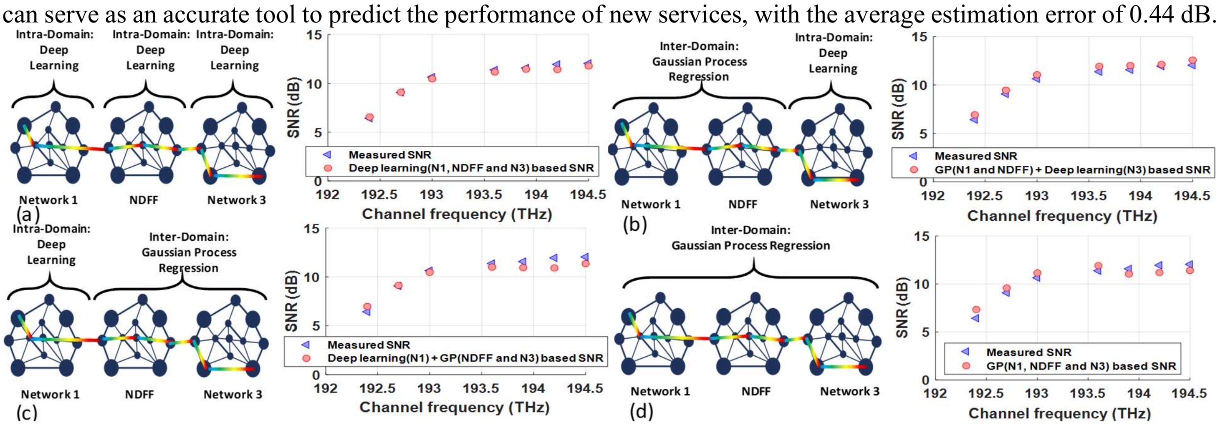

Fig. 6. The accuracy analysis of the proposed multi-domain hybrid learning based abstraction with spectrum occupation of the allocated links in network 1 in Fig. 4 (a) and allocated links in NDFF and network 3 are fully occupied with all 24 channels.

4. Conclusion

In this paper, we propose a hybrid learning assisted abstraction model in the optical networks for new services performance evaluation before provisioning. The results verify the accuracy of the proposed learning framework with the presence of different available training data sets.

5. Acknowledgement

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6. References

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